DECISION SUPPORT SYSTEM FOR INDIVIDUALIZING RADIOTHERAPY DOSE

RELATED APPLICATION

[0001] The present patent document claims the benefit of the filing date under 35 U.S.C. § 119(e) of Provisional U.S. Patent Application Ser. No. 62/791,915, filed Jan. 14, 2019, and is a continuation in part of U.S. patent application Ser. No. 16/270,743, filed Feb. 8, 2019, which claims the benefit of the filing date under 35 U.S.C. § 119(e) of Provisional U.S. Patent Application Ser. No. 62/677,716, filed May 30, 2018, 62/745,712, filed Oct. 15, 2018, all of which are hereby incorporated by reference.

BACKGROUND

[0002] The present embodiments relate to decision support for therapy. One typical example is the application in radiotherapy. Radiotherapy is a useful and cost-effective treatment strategy for many types of cancer. Although radiotherapy is an effective cancer treatment, a large portion of patients subsequently experience radio-resistance and recurrence of their cancers. Doctors seek to select treatments based on specific characteristics of the patient and their disease to avoid treatment resistance and recurrence.

[0003] Predictors of radiation response are largely limited to clinical and histopathologic parameters. Molecular characterization using genomic and proteomic technologies is limited due to spatial and temporal heterogeneity of tumors. The tumors usually require biopsies and invasive surgeries to extract and analyze small portions of tumor tissue, which does not allow for a complete characterization of the tumor. Medical imaging can provide a more comprehensive view of the entire tumor in an ongoing basis to monitor the development and progression of the tumor or its response to therapy. Imaging is noninvasive and is already often repeated during treatment in routine practice.

[0004] Predictive information personalized to a patient may be extracted from medical imaging. One example is the treatment selection for non-small cell lung cancer (NSCLC). Stereotactic body radiation therapy (SBRT) is the standard of care for medically inoperable patients with early-stage NSCLC. However, different patterns of failure (local recurrence or distant recurrence) can be observed after SBRT. Moreover, when patients undergo repeat SBRT or salvage therapy, the outcomes are significantly worse. Standard approaches for radiotherapy that demonstrate efficacy for a population may not achieve optimal results for individual patients. An unmet clinical need is to predict as early as possible the potential outcome. For instance, if the patients are divided into two groups of responders and non-responders based on some prognostic or predictive biomarker, a series of strategies could be followed to further change the response pattern. The treatment parameters or treatment sequence and modality may be changed in the treatment strategy for patients in the non-responder group.

[0005] In clinical practice, tumor response to therapy is only measured using one- or two-dimensional descriptors of tumor size (RECIST and WHO, respectively). Although the tumor size measured in follow-up scans can indicate response to therapy, it often does not provide enough predictive information to the outcome of therapy.

[0006] In radiomics, digital medical images are converted to high dimensional data for improved decision support. The hypothesis is that biomedical images contain information that reflects underlying pathophysiology and that these relationships can be revealed via quantitative image analyses. The practice of radiomics typically involves extraction and qualification of descriptive features from the volume and application of a model to predict outcome from the descriptive image features. In classical radiomic analysis, the image features that can describe various tumor physical and geometrical characteristics are pre-defined and can be computed using different mathematical formulas (handcrafted features). These features usually quantify characteristics about tumor intensity, shape, texture, and wavelet transformation focusing on the frequency domain. The radiomics analysis may fail to maximize the information obtained where a very large number of features are usually extracted from images which contain lots of redundant or irrelevant information. Handcrafted radiomic features are in pre-defined groups so it is likely that some predictive information is not fully captured by the pre-defined features.

SUMMARY

[0007] Systems, methods, and instructions on computer readable media are provided for decision support in a medical therapy. Machine learning provides a machine-learned generator for generating a prediction of outcome for therapy personalized to a patient. Deep learning may result in features more predictive of outcome than handcrafted features. More comprehensive learning may be provided by using multi-task learning where one of the tasks (e.g., segmentation, non-image data, and/or feature extraction) is unsupervised and/or draws on a greater number of training samples than available for outcome prediction alone.

[0008] The outcome prediction may be used to determine individualized dose. To assist in decision support, a regression analysis of the cohort used for machine training or other cohort relates the outcome from the machine-learned generator to the individualized dose and an actual control time (e.g., time-to-event). The dose that minimizes side effects while minimizing risk of failure to a time for any given patient is determined from the outcome for that patient and a calibration from the regression analysis.

[0009] In a first aspect, a method is provided for decision support in a medical therapy system. A medical scan of a patient is acquired. A prediction of outcome from therapy for the patient is generated. The outcome is generated by a machine-learned multi-task generator having been trained based with both image feature error and outcome error. A dose for the patient is determined based on a calibration relating the outcome, the dose, and a time-to-event. An image of the dose is displayed.

[0010] In various embodiments, the calibration is a regression from a cohort used to train the machine-learned multi-task generator. For example, the regression is a Fine and Gray regression. The calibration may be based on estimation of a cumulative incidence function. The dose may be modeled as a continuous variable in the calibration. The calibration may be a nomogram.

[0011] In one embodiment, the dose is determined to provide the outcome as a probability of failure of less than 5%. The dose identified to provide the outcome in a given value, such as less than 5% failure of therapy, for a given value of the time-to-event, such as 12 months.